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Entry and exit in severe recessions: lessons from the 2008–2013 Portuguese economic crisis

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Abstract Under cleansing, productivity-enhancing reallocation is expected to be accelerated in recessions. In this paper we contribute to the analysis of one component of the national systems of entrepreneurship (namely capital market frictions) by showing that in the extreme scenario of deep recession efficiency in resource reallocation can actually be reduced. Using data from the pronounced Portuguese economic crisis, we do find a spike in firm exit in 2008–2012 vis-à-vis the 2004–2007 pre-crisis period, and a substantial increase in job destruction as well. But we did not find any strong evidence that job reallocation is counter-cyclical, while a non-negligible fraction of high-productivity firms actually shut down. In turn, our selected proxies for strictness in credit markets reveal that in deep recessions they are seemingly associated with increased firm exit and lower employment creation. Taken in round, our results show that credit market stringency in conjunction with an unfavourable economic cycle is likely to generate a long-lasting destructive process.

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1 Introduction

The national systems of entrepreneurship theory suggest that economic growth is driven by the process of resource allocation towards an efficient use, which in turn is driven by entrepreneurial decisions made by individuals embedded in a country-level context (Acs et al. 2014). In the past few years, the study of productivity issues has undoubtedly shown that a large percentage of the observed productivity growth can be credited to firm-level reallocation, with low-productivity firms losing market share (or shutting down) in favour of more productive incumbents and new entrants (e.g. Foster et al. 2001; Carreira and Teixeira 2008). Moreover, the Schumpeterian literature has suggested that "cleansing", that is, the mechanism that replaces less by more efficient firms, is counter-cyclical, based on the argument that resource reallocation seems to be more intense during recessions (e.g. Davis and Haltiwanger 1992; Caballero and Hammour 1994). Rather than cleansing, however, some other studies have emphasized the role of distortions in credit and labour markets on reallocation dynamics in recessions (e.g. Barlevy 2002, 2003; Caballero and Hammour 2005).

Dominant or not in recessions, it is still not clear how the cleansing mechanism really works in "severe" recessions simply because they are a rare event. The theory of the firm offers conflicting predictions on how the two major facets of recessions—that is, demand downturn and strict financial constraints—affect firm behaviour, and in this context the 2008–2013 Portuguese crisis, for its nature and length, seems to offer a quite natural experiment. The issue is crucial as it serves to designing better policies: if crises generate "counterproductive destruction", then countercyclical policies have the potential to ameliorate the prospects of sustained long-run growth; on the contrary, if crises generate "productive cleansing", then countercyclical policies entail the risk of hampering economic recovery. Since national systems of entrepreneurship are expected to provide favourable context factors (e.g. availability of external resources and access to markets; Acs et al. 2015, p. 16), confirmation of either of the two hypotheses has important policy implications.

The main objective of this paper is to provide new evidence on how the market selection mechanism works in severe recessions. The central hypothesis is that during financial crisis credit market distortions reduce the efficiency of resource reallocation through reduced bank lending to profitable projects. Banks may also forbear bad debtors, delaying the process of firm death, in an effort to protect their own balance sheets, thereby hindering one of the key mechanisms through which productivity growth arises. In other words, when financial markets are seriously distorted, reallocation may be driven predominantly by financial constraints rather than by raw market variables such as productivity, demand, and costs.

Our empirical enquiry is based on a newly assembled panel of Portuguese firms, covering the 2004–2012 interval. The dataset covers the population of Portuguese firms (of all size groups) operating in the manufacturing sector. To our knowledge, this paper is the first to explicitly study the nexus between financial crisis and productivity growth at micro-level in a developed economy, a critical issue given the importance of understanding the dynamic components of national systems of entrepreneurship.

Our main finding is that evidence does not unequivocally support the cleansing hypothesis. We found an exceptional strong exit flow of firms during the crisis and an increase in the job destruction rate; but job reallocation has not proven to be countercyclical. In line with the cleansing paradigm, the decomposition of aggregate productivity growth does suggest that low-productivity continuing firms contract their market shares during the crisis. However, we also found that a non-negligible fraction of high-productivity firms (some of which are very large) actually shut down, a result that we interpret as a major market selection failure. Finally, even if the risk of exit of low-productivity firms increases in severe recessions, credit market conditions per se seem to play a major role on firm exit and employment growth.

The paper is organized as follows. Section 2 presents an overview of the literature on firm dynamics and industry productivity growth. It also includes a description of the main events of the Portuguese financial crisis. Section 3 discusses the methodology and describes the dataset, while the main empirical results and their discussion are presented in Sect. 4. Section 5 concludes.

2 Background

2.1 Related literature

The Schumpeterian process of "creative destruction", wherein innovations introduced by entrepreneurs can be taken as business experiments subject to the market test, and firm exit as a necessary selection mechanism through which non-competitive technologies and products are excluded, provides an adequate theoretical framework to the study of how firm dynamics actually contributes to productivity growth. Although Schumpeter (1934a) has highlighted the role of the entrepreneurship in an economic context, the subsequent entrepreneurship literature has focused mostly on entrepreneurs, with the role of the macro environment being largely ignored. To address this gap, Acs et al. (2014, 2015) propose the theory of national systems of entrepreneurship, in which it is emphasized the multiple and complex interactions between individual and contextual factors. In this framework, the resource allocation process is driven by individual-level decisions, but these decisions, and the corresponding outcomes, are conditioned by a multifaceted economic, social and institutional context. At the aggregate level, the outcome of these decisions is resource reallocation towards activities with an increasing value-added that ultimately leads to a higher productivity growth. Presumably, this productivity-enhancing reallocation can be impaired by "bottleneck factors" such as availability of external resources and access to credit markets, a central aspect of our discussion in this paper.

As a matter of fact, several country-studies reveal that entry and exit flows of firms are very substantial. Furthermore, entry and exit tend to be highly (positively) correlated. The main reason is that the rate of early mortality among new firms is very high. Entrants are typically small, but successful entry tends to generate rapid grow. On average, they double their initial size after 6–7 years, although it may take more than a decade to achieve the average size of established firms (Audretsch and Mata 1995; Geroski 1995; Caves 1998). Earlier research also found a close connection between firm dynamics and productivity, with exit, in particular, being much more common among low-productivity firms, while firm growth correlates positively with productivity (Caves 1998; Carreira and Teixeira 2011a).

Firm mobility is expected to have an impact on aggregate productivity growth, with changes in industry-level productivity arising either from within-firm productivity growth (e.g. based on innovation) or resource reallocation (through firm growth, exit, and entry). Baily et al. (1992), for example, found that the contribution of increasing (decreasing) output shares of high (low)-productivity continuing plants was the main source of the US industry productivity growth in the period 1972–1987, while the entry and exit contribution was found to be very small. Using a different decomposition method for the period 1977–1992, Foster et al. (2001) showed that resource reallocation accounted for half of the manufacturing productivity growth, of which about 18 % was due to the net entry effect. These results were confirmed by many authors for several countries (e.g. Disney et al. 2003; Baldwin and Gu 2006; Cantner and Krüger 2008; Carreira and Teixeira 2008).

An ongoing debate is whether in recessions the productivity-enhancing reallocation is accelerated (the "cleansing" effect). The genesis of the debate can be traced back to the Schumpeterian process of creative destruction: recessions imply outdated techniques and products being driven out of the market at a more accelerated pace so that resources are freed to more productive uses (Schumpeter 1934b). This approach has been taken by different theoretical models such as in Caballero and Hammour (1994, 1996) and Mortensen and Pissarides (1994). Empirical evidence also seems to support the idea that recessions intensify resource reallocation (Davis and Haltiwanger 1992; Davis et al. 1996) and generate productive cleansing (Foster et al. 2001; Carreira and Teixeira 2008).

Recent theoretical studies have suggested, however, that the cleansing effect may be reversed by many other aspects, namely financial and labour market frictions (Barlevy 2002, 2003; Caballero and Hammour 2005). Barlevy (2003), for example, deploys a model where recessions tend to be cleansing only in the absence of financial constraints. Since the best projects generally require a higher level of investment, there might be indeed a shift towards the funding of projects that are less productive (and less financially demanding) in times of tight financial constraints.

The scope of present study is slightly different. We focus on the pattern of productivity dynamics in severe recessions (or economic crises), which is rarely examined in this context. One comparable exercise was conducted by Griffin and Odaki (2009) who, using data on large manufacturing firms between 1969 and 1996, found that the weak Japanese productivity growth during the long 1990s stagnation was due to a significant reduction in the within-firm effect rather than to an absence of cleansing. Hallward-Driemeier and Rijkers (2013) also evaluated the effect of the 1997 Asian crisis using plant-level data from Indonesia. Despite a spike in firm exit and an increased employment reallocation rate, these authors did not find evidence supporting the cleansing effect either. Productivity was indeed less critical for firm survival during the crisis, while the risk of exit increased for those firms financially constrained. Finally, Foster et al. (2014) investigated the reallocation dynamics among US manufacturing firms during the 2007–2009 Great Recession. They found that the Great Recession has been less productivity enhancing in comparison with previous recessions and, in particular, that the extent of the cleansing effect was less pronounced than it was expected.

2.2 The Portuguese crisis

The Portuguese economic crisis began with the 2008 financial crisis and has persisted until 2013 in connection with the European sovereign debt crisis. Over this period, as shown in Fig. 1, the real gross domestic product (GDP) growth rate followed a “W” pattern. Indeed, the austerity measures adopted after the 2011 international financial assistance program (the so-called “Memorandum of Understanding”, negotiated between the Portuguese government and the European Commission, the European Central Bank and the International Monetary Fund) in a context of a global downturn triggered a severe domestic recession, followed by a dramatic increase in the unemployment rate that more than doubled the pre-crisis level.

The financial-sovereign debt crisis and the subsequent measures of the “Memorandum of Understanding” generated severe credit restrictions for the Portuguese non-financial firms, as shown in Fig. 2. Although the channels through which credit market

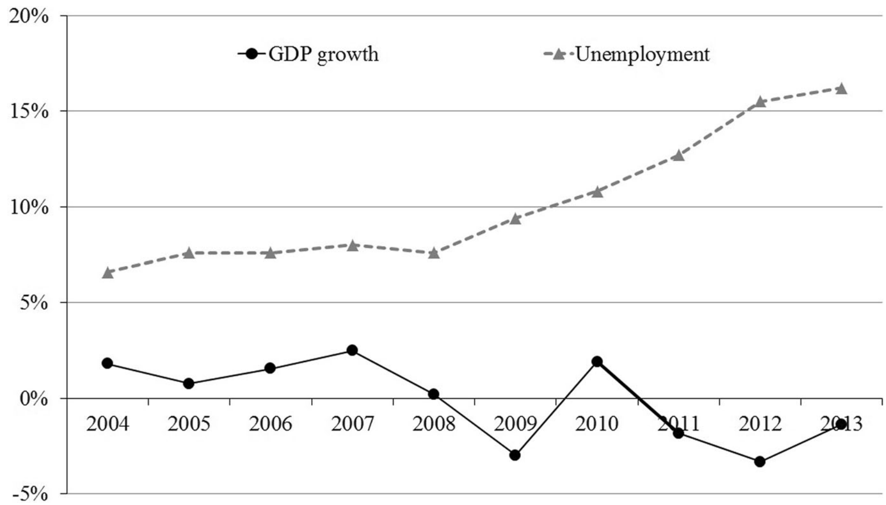

Fig. 1 Real GDP growth and the rate of unemployment. *Source*: PORDATA

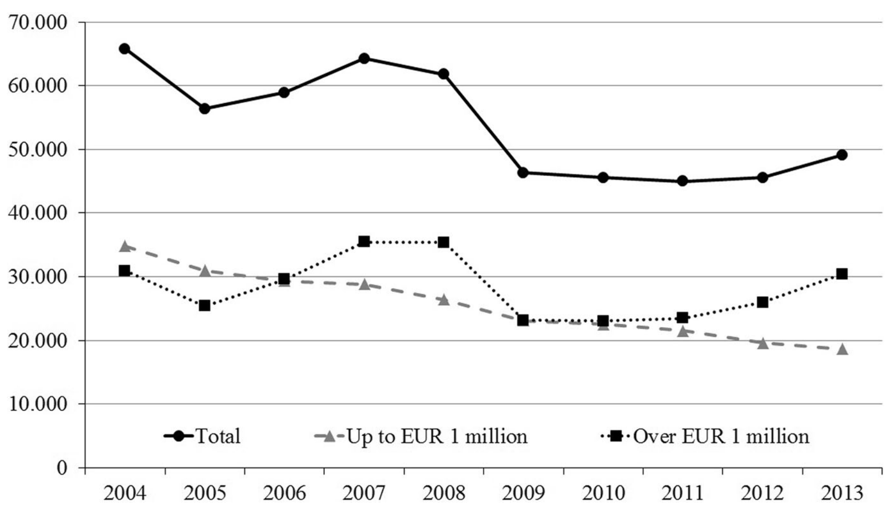

Fig. 2 Loans to non-financial firms. *Source*: PORDATA. *Note*: Values in millions of Euro

distortions affect firm performance and aggregate productivity are diverse, credit constraints and bank forbearance have been identified as the most relevant. Credit constraints affect (heterogeneous) firms differently. In particular, credit constraints may not only prevent high-productivity firms that are financially constrained from expanding their profitable projects (and eventually causing exit), but also deter entry of new firms that require a substantial initial capital outlay. There may also be an indirect effect via reduction in the competitive pressure on incumbent firms, deferring downsizing and exit of low-productivity firms that just happen to be not financially constrained (Aghion et al. 2009; Carreira and Teixeira 2011b).

Bank forbearance is another channel through which credit market restrictions are able to distort resource reallocation across firms. Indeed, banks may be tempted to fund "zombie" firms so that they look artificially solvent on their own balance sheets. This behaviour was common among Japanese banks during the early 1990s (Peek and Rosengren 2005; Caballero et al. 2008).

3 Hypotheses and methodology

3.1 Industry-level analysis

The studies outlined above yield competing predictions at both industry and firm level. If the allocative efficiency channel is an important mechanism through which financial crises affect economic performance, then some particular productivity changes at industry-level should be observed. According to the cleansing hypothesis, less productive firms are expected to contract further or even exit in response to a strong negative shock. In other words, the importance of the changes in market share and exit to aggregate productivity growth is expected to increase. By contrast, credit constraints and bank forbearance are expected to reduce these two effects. But credit constraints may also reduce the within-firm contribution, albeit indirectly, as competition is reduced to incumbent firms. We have therefore our first set of hypotheses:

Hypothesis 1 Under stringent credit constraints, severe recessions do not increase job reallocation.

Hypothesis 2 Severe recessions are times of counterproductive destruction, resulting from declining market shares and exit of (financially constrained) high-productivity firms.

To assess whether productive cleansing or counterproductive destruction is dominant, we decompose the aggregate productivity growth using an extended version of the Olley and Pakes (1996) decomposition method proposed by Melitz and Polanec (2015)—the dynamic Olley–Pakes decomposition hereafter:

$$\Delta P_t = \Delta \bar{P}_{Ct} + \Delta \mathrm{cov}_{Ct}(\theta_{it}, p_{it}) + \theta_{Et}(P_{Et} - P_{Ct}) + \theta_{X(t-\tau)}\left(P_{C(t-\tau)} - P_{X(t-\tau)}\right), \quad (1)$$

where P_t represents the industry productivity level in year t; Δ denotes changes between t–τ and t; and C, E, and X denote the group of continuing, entering, and exiting firms (the group of continuing firms comprises all existing firms in the beginning of the year that remain active throughout the year). θ_{it} is the market share (i.e. the real gross output share) of the ith firm in year t, and p_{it} is the corresponding productivity level (i.e. firm-level total factor productivity, as explained in Sect. 3.4 below); θ_{gt} is the share of group g and P_{gt} and $\bar{P}_{gt}$ are the corresponding weighted and unweighted average productivity ($g = C, E, X$). The first term on the right-hand-side of Eq. (1)—the "within" term—captures the contribution of within-firm productivity changes of continuing firms. The second term—the "covariance" term—reflects the inter-firm resource reallocation towards more productive continuing firms. The last two terms capture the contribution of entering and exiting firms, respectively. The entry (exit) contribution is positive if the productivity level of entering (exiting) firms is higher (smaller) than the productivity level of continuing firms in the corresponding year.

3.2 Firm-level analysis

At firm level, if the cleansing effect is dominant, then recessions are expected to accelerate downsizing and exiting of low-productivity firms, which in turn results in a stronger correlation between productivity and employment growth, on the one hand, and survival on the other. However, according to the credit constraint and bank forbearance perspective, financial crises may lead to further restrictions on bank lending to profitable operations, thereby contributing to lower firm growth or higher exit. A second effect via reduction in the competitive pressure from financially constrained firms is also possible, with low-productivity firms that are not financially constrained maintaining their market shares. We have therefore two additional hypotheses:

Hypothesis 3 High-productivity firms do exit during financial crisis, while less productive firms, but not financially constrained, survive.

Hypothesis 4 Employment change becomes more strongly (negatively) associated with financial constraints in deep recessions.

In order to analyse the determinants of exit, we estimate a survival model in which survivability is a function of firm productivity, p_{it}, a set of firm financial characteristics, fc_{it}, and firm and industry control variables, x_{it} and z_j, respectively. Additionally, and in order to assess the effect of the crisis on the selected outcome, we generated the interaction terms crisis $\times$ p_{it}, and crisis $\times$ fc_{it}, where crisis is a dummy variable equal to 1 if year t belongs to 2008–2012, 0 otherwise. Our implementation follows a semi-parametric Cox Proportional Hazards model—CPH hereafter (Cox 1972; see also Carreira and Teixeira 2011a, for further details on a similar implementation):

$$h_i(t) = h_{0i} \exp\big(\beta_p p_{it} + \beta_{cp}\text{crisis} \times p_{it} + \beta_{fc} fc_{it} + \beta_{cfc}\text{crisis} \times fc_{it} + \beta_x x_{it} + \beta_z z_j + u_{it}\big), \quad (2)$$

where h_{0i} is the baseline hazard function and u_{it} is a standard error term. β_p is expected to be negative, that is, the higher the productivity level, the lower the risk of exiting; and under the hypothesis that a crisis intensifies the creative destruction process, we should expect $\beta_{cp} > 0$. (Note that under the null hypothesis of no regime shift, we have $e^{\beta_{cp}} = 1$, that is, $\beta_{cp} = 0$.)

There is no clear methodology to evaluate whether firms are financially constrained and the corresponding level (Carreira and Silva 2010; Silva and Carreira 2012). We use three variables to capture different aspects of firm's financial performance: sales, operating cash-flow and leverage. The variable *Sales*, normalized by firm size (that is, by the number of employees), captures the firm's potential capacity to finance its investments. A higher value of ongoing revenue means that a greater fraction of investment can be financed by internal funds and represents a lower level of external funds needed. *Operating cash-flow* captures existing liquidity and is proxied by the operating income variable. Typically, recessions put additional pressure on firm liquidity and, as a consequence, firms may hold their available liquidity rather than investing. *Leverage* is measured by the book debt to assets ratio and proxies the dependence from firm external financing. In this context, highly leveraged firms are more vulnerable during recessions and, as a result, their investment demand is expected to decline. Thus, financially constrained firms are expected to shut down more often. That is: firms with a higher sales volume or a higher operating cash-flow have a reduced risk of exiting, which implies $\beta_{fc(\text{sales})} < 0$ and $\beta_{fc(\text{operating cash-flow})} < 0$. In turn, a higher leverage ratio implies a higher risk of failure (or $\beta_{fc(\text{leverage})} > 0$). Additionally, financially constrained firms are more vulnerable to credit market restrictions during the crisis, and therefore we should expect a negative sign in the case of the interaction between *crisis* and *sales* and between *crisis* and *operating cash-flow* ($\beta_{cfc(\text{crisis} \times \text{sales})} < 0$ and $\beta_{cfc(\text{crisis} \times \text{operatingcash-flow})} < 0$, respectively); and a positive sign in the case of the interaction with *leverage* ($\beta_{cfc(\text{crisis} \times \text{leverage})} > 0$).

The model specification (2) includes additional variables such as firm size, measured as the natural logarithm of the number of employees, and the entry rate, the latter being introduced in order to capture the competitive effect of new firms. We also control for other (non-observed) differences across industries by including a set of industry dummies.

Finally, to assess whether the change in employment of continuing firms is strongly associated with firm's productivity (and firm's financial constraints), we estimate the following model[1]:

$$\Delta L_{i(t+1)} = \varphi_p p_{it} + \varphi_{cp}\text{crisis} \times p_{it} + \varphi_{fc} fc_{it} + \varphi_{cfc}\text{crisis} \times fc_{it} + \varphi_x x_{it} + \varphi_z z_j + d_t + v_i + u_{it}, \quad (3)$$

where $\Delta L_{i(t+1)}$ is the employment change between t and $t+1$, d_t denotes year dummies, v_i is a firm-fixed effect and u_{it} is a standard error term.

[1] Following Hallward-Driemeier and Rijkers (2013) and Carneiro et al. (2014), we use the same set of explanatory variables as in the survival model above.

3.3 Data

Our data are based on a new dataset extracted from *Sistema de Contas Integradas das Empresas* (SCIE), an annual—and mandatory—business survey administrated by the Portuguese Statistical Office (INE). The SCIE comprises the 2004–2012 interval and includes all registered enterprises in Portugal. In particular, it contains detailed input and output information required for the computation of firm-level productivity.

Each firm in the SCIE database has a fixed identification number. Every single unit can therefore be easily followed longitudinally, with births having a distinct identification number. Prior to the beginning of production, however, there is in general an initial investment period, which may extend beyond the first year of life. Since we are only concerned with active firms, for any unit created in $t–\tau$, if there is no production recorded between $t–\tau$ and t, then t is defined as the birth year. There is also a number of re-entries over the sample period. We treat these cases as new entrants. In turn, all the exits from the database are flagged as firm deaths. If a given unit ceases production before the year of the registered death, say $t + \tau$, and no production is observed between t and $t + \tau$, t is coded as the year of death.

The SCIE dataset offers many advantages. First, the raw survey is assembled at firm rather than plant level. The firm is typically the key unit regarding the most relevant managerial decisions. Second, the panel length (i.e. a maximum of 9 consecutive years) allows us to follow firm performance over a sufficiently long period, including the pre-crisis period. Finally, the SCIE covers the entire population of Portuguese firms.

The main weakness of the SCIE is the lack of information concerning mergers and acquisitions. We cannot distinguish a true exit from an exit generated by a merger or acquisition. Similarly, we cannot distinguish a new entrant from the case in which a new firm is just the result of a merger.

We excluded from the dataset highly concentrated industries, namely *tobacco products*, and *coke and refined petroleum products*. Firms with missing observations or unreasonable values (e.g. a negative value of *total net assets*, *cost of materials* or *services purchased*) were also ignored. Table 1 presents the lists of industries covered by the present study and the corresponding number of firms. Our estimation sample comprises an unbalanced panel of 56,849 firms or 333,375 year-firm observations.

3.4 Measurement of productivity

Firm-level total factor productivity (TFP) is our selected productivity measure. To compute the TFP, we firstly estimate the factor elasticity parameters of a Cobb–Douglas production function for each industry (at two-digit level), to allow for sector heterogeneity (see Bartelsman and Doms 2000, for a discussion of alternative TFP measures):

$$y_{it} = \alpha_0 + \alpha_K k_{it} + \alpha_L l_{it} + \alpha_M m_{it} + u_{it}, \tag{4}$$

where y_{it} is the real gross output of the ith firm in year t, and k_{it}, l_{it} and m_{it} are capital, labour and material (intermediate) inputs, respectively (all variables in logarithms); and α_f denotes factor elasticities, $f = K, L, M$. Note that we do not impose any restriction on the sum of the three factor elasticities.

The *gross output* is given by the sum of total revenues from sales and services rendered, self-consumption of own production and production subsidies. It is deflated by the producer price index at the three-digit industry level (or two-digit level when the former is unavailable). The *labour* input is a 12-month employment average. *Materials* include the cost of materials and services purchased and were deflated by the intermediate consumption price index at the two-digit level (or the GDP deflator index when unavailable). *Capital* is measured as the book-value of total net assets, that is, it includes not only tangible and intangible assets but also all other elements of the asset side of the balance sheet, including accounts receivable and inventory investment, all important to the operation of the firm. For the first year in the time-series of a firm, we have deflated all the assets by the GDP deflator index of that year (2004 base-year), in order to derive the capital stock K_t. For subsequent years, if the book-value of assets rises, then the increment is deflated by GDP deflator index of the current year and added to the $K_{t–1}$ to yield K_t. If it declines, K_t is reduced proportionately. Output and input variables are measured in constant 2004 Euro.

To estimate Eq. (4), we assume $u_{it} = \omega_{it} + \eta_{it}$, with ω_{it} denoting a firm-specific unobserved component and η_{it} a residual term uncorrelated with input choices. Ordinary least-squares estimation produces inconsistent estimates due to the likely presence of

Table 1 Number of firms by industry

CAE	Industry	Shortcut	Mean	SD
10	Food products	Food	4952	96.7
11	Beverages	Beverages	663	51.9
13	Textiles	Textiles	2036	213.5
14	Wearing apparel	Apparel	4656	628.5
15	Leather and related products	Leather	1750	60.4
16	Wood and products of wood and cork (except furniture)	Wood	2755	242.2
17	Pulp, paper and paper products	Paper	395	24.9
18	Printing and reproduction of recorded media	Printing	2093	125.4
20	Chemicals, chemical products and man-made fibres	Chemicals	452	27.3
21	Pharmaceutical products	Pharmaceutical	111	6.7
22	Rubber and plastic products	Rubber	910	24.4
23	Other non-metallic mineral products	Other non-metallic	2630	233.7
24	Basic metals	Basic metals	261	16.9
25	Fabricated metal products (except machinery/equipment)	Metals	6291	194.5
26	Computer, electronic and optical products	Computer	210	16.4
27	Electrical equipment	Electrical	511	32.3
28	Machinery and equipment n.e.c.	Machinery	1194	88.8
29	Motor vehicles, trailers, semi-trailers and accessories	Motor vehicles	418	14.6
30	Other transport equipment	Other transport	155	15.5
31	Furniture	Furniture	2441	183.2
32	Other manufacturing activities	Other manufacturing	1345	65.9
33	Repair and installation of machinery and equipment	Repair	1554	150.6

The decomposition uses the two-digit level of the Portuguese Classification of Economic Activities (CAE-Rev.3). At least at this disaggregation level there is a direct correspondence between this classification and the classifications of both the European Community (NACE-Rev.2) and the United Nations (CITA-Rev.4). Mean values over the period 2004–2012 and standard deviations (SD) of the number of firms

simultaneity and selection biases. The simultaneity bias arises because input demand functions are also determined by firm's knowledge of its productivity level. The selection bias is generated by endogenous exit, as smaller firms, with lower capital intensity, are more likely to exit. Assuming that ω_{it} is time invariant, Eq. (4) can be estimated using the least square dummy variable approach or the within transformation.[2] Consistency of the fixed effect model requires, however, strict exogeneity of the included regressors, which is a non-realistic assumption (Griliches and Mairesse 1998). To overcome this problem, we estimate Eq. (4) using the semi-parametric estimation method proposed by Olley and Pakes (1996).[3] This method accounts for the endogeneity of input demand and the selection bias problem, thus improving the quality of the estimation.[4]

Finally, the (log) TFP is defined as the difference between firms' output and the weighted sum of inputs:

$$\hat{p}_{it} = y_{it} - \hat{\alpha}_K k_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it}. \tag{5}$$

4 Results

4.1 Firm mobility and job flows

Our analysis divides the sample into two sub-periods: pre-crisis (2004–2007) and crisis

[2] The random effects model is rejected in favour of the fixed-effects model by the Hausman test at the 1 % significance level.

[3] Estimation was performed using the *opreg* command of Stata SE 11.2, developed by Yasar et al. (2008).

[4] There are alternative ways for the computation of factor elasticities (Beveren 2012). However, they all tend to generate similar TFP results, even if they produce somewhat different elasticities (Syverson 2011).

(2008–2012). Table 2 reports the average entry and exit rates by industry, while Fig. 3 plots their evolution for the entire manufacturing sector. As it is apparent, there is a quite substantial firm mobility: on average, 6.2 % of the firms operating in year t were not producing in $t-1$, while 7.9 % of firms operating in $t-1$ do not produce at all in t, which implies a turnover rate of 14.1 %. The annual entry and exit rates vary considerably across industries. In particular, *Repair* presents the highest average entry rate, at 8.9 %, while the lowest entry rate is in *Other non-metallic*, at 4.3 %. *Apparel* and *Beverages* show the highest and the lowest average exit rates, at 12.0 and 3.7 %, respectively. The figures are broadly confirmed by other studies (see Caves 1998; Bartelsman et al. 2005).

Table 2 Entry and exit rates by industry (in percentage)

	Pre-crisis		Crisis	
	Entry rate	Exit rate	Entry rate	Exit rate
Food	6.5	4.9	6.1	6.1
Beverages	5.7	3.0	6.5	4.0
Textiles	6.2	8.5	5.5	9.9
Apparel	7.1	10.9	7.9	12.7
Leather	8.1	10.3	8.6	8.0
Wood	5.6	8.2	5.9	8.9
Paper	5.2	7.0	5.5	7.7
Printing	6.9	7.3	5.2	8.3
Chemicals	5.7	6.4	5.4	7.1
Pharmaceutical	8.5	4.7	5.9	5.2
Rubber	4.8	5.1	4.9	6.3
Other non-metallic	4.7	6.7	3.9	8.0
Basic metals	5.2	6.9	5.9	7.1
Metals	6.1	6.8	5.3	6.7
Computer	7.8	11.0	7.2	8.2
Electrical	5.4	8.6	5.4	7.1
Machinery	5.3	7.5	4.5	7.0
Motor vehicles	5.5	5.7	4.5	6.3
Other transport	8.7	11.5	8.0	9.5
Furniture	6.2	7.6	6.2	9.6
Other manufact.	6.8	7.9	5.9	7.7
Repair	7.8	3.3	9.5	7.1

The reported entry (exit) rate is calculated as the ratio of entering (exiting) firms to the total number of firms in t ($t-1$), as suggested by Dunne et al. (1988). The pre-crisis (crisis) period is defined as 2004–2007 (2008–2012). The corresponding values by year are given in Table 11

Comparing the two selected periods, the main picture that emerges is that while the crisis seems to have no obvious impact on the average entry rate, the average exit rate is about 0.7 % points higher than in the crisis period, with a peak in 2011, at 9.9 %. Looking across industries, *Repair* shows the highest exit rate difference between the two sub-periods, at 3.8 % points, while in one-third of industries the exit rate is stable.

Panel (a) of Table 3 contains the survival rate for each entry cohort, while panel (b) reports the corresponding hazard rate. There are three notable results. First, survival rates at birth are low: on average, around 24 % of entrants fail within the two subsequent years and only approximately half of the entrants in a given year survive beyond the fifth year. This pattern is robust to sector disaggregation, but with seemingly differences: in *Other transport equipment* only 30 % of entrants in a given year survive beyond the fifth year, while in the case of *Beverages* the corresponding rate is 74 % (these values are reported in Table 12). Second, the hazard rate for entrants does not necessarily rise with age. The hazard rates in panel (b) of Table 3 indicate that entrants exit at an approximately constant rate of 12 % per year. Finally, the crisis seems to have an impact on the survival probability of new firms, with the corresponding hazard rate increasing in 2011 by a notorious 3.7 % points for all entry cohorts.

Figure 4, and Tables 4 and 5 present the corresponding job creation and job destruction rates. In Fig. 4, the average job creation over the entire sample period is 6.7 %, while average job destruction is 9.7 %, with the negative net job creation shifting from −1.7 %, in the pre-crisis period, to −3.7 % during the crisis. The higher (negative) net job creation during the crisis was driven by a slowdown in job creation (−0.7 % points) and an increase in job destruction (+1.3 % points). Moreover, as observed by Carneiro et al. (2014), there is a “catastrophic” net job loss in 2009 of −6.5 %, mostly due to a massive job destruction (at 11.8 %), but also due to a much reduced rate of job creation as shown in Table 13 in “Appendix”. All in all, and ignoring the two first years of the sample period, the pattern of job reallocation (i.e. the sum of job creation and job destruction flows) in Fig. 4 is quite flat. In turn, the share of job creation

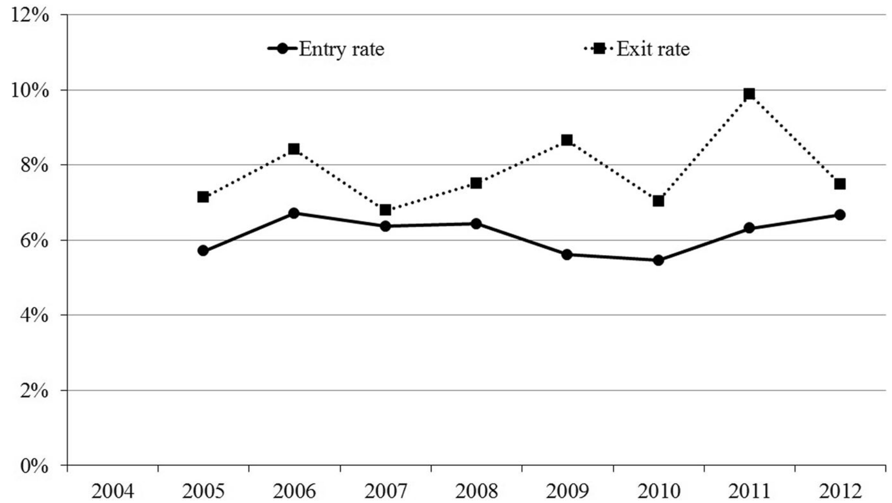

Fig. 3 Firm entry and exit

Table 3 Survival and hazard rates by entry cohort (in percentage)

	2004	2005	2006	2007	2008	2009	2010	2011	2012
Survival rates									
2004 Entry cohort	100	90.7	79.3	71.5	65.2	58.0	52.5	46.6	43.0
2005 Entry cohort		100	85.3	75.0	67.6	59.5	54.3	47.4	43.4
2006 Entry cohort			100	87.6	77.5	67.7	60.4	50.4	45.8
2007 Entry cohort				100	86.1	72.8	65.5	54.5	48.5
2008 Entry cohort					100	85.9	75.6	64.4	57.8
2009 Entry cohort						100	90.3	75.7	67.7
2010 Entry cohort							100	85.8	77.3
2011 Entry cohort								100	89.0
Hazard rates									
2004 Entry cohort		9.3	12.6	9.9	8.8	10.9	9.5	11.3	7.7
2005 Entry cohort			14.7	12.1	9.9	12.0	8.7	12.7	8.4
2006 Entry cohort				12.4	11.5	12.7	10.8	16.5	9.2
2007 Entry cohort					13.9	15.5	10.0	16.8	11.0
2008 Entry cohort						14.1	12.0	14.9	10.2
2009 Entry cohort							9.7	16.2	10.6
2010 Entry cohort								14.2	9.9
2011 Entry cohort									11.0

The reported survival rates for each entry cohort are the ratio of the number of surviving firms to the respective number of entering firms. The hazard rates for each entry cohort are the ratio of the number of deaths each year to the number of surviving firms in previous year. The corresponding values by industry are given in Table 12

(destruction) flows due to firm entry (exit)—the JC entrants and JD exits series in Fig. 4—is slightly smaller (larger) in the crisis period, which is consistent with the reported entry and exit behaviour shown in Table 4, with half of the 2011 job destruction being due to exit. Finally, micro- and small firms account for roughly 60 % of all observed job flows, a pattern that seems unchanged over the crisis as shown in Table 5.[5]

[5] We follow the European Commission enterprise size classification, where micro firms are those with <10 employees, small

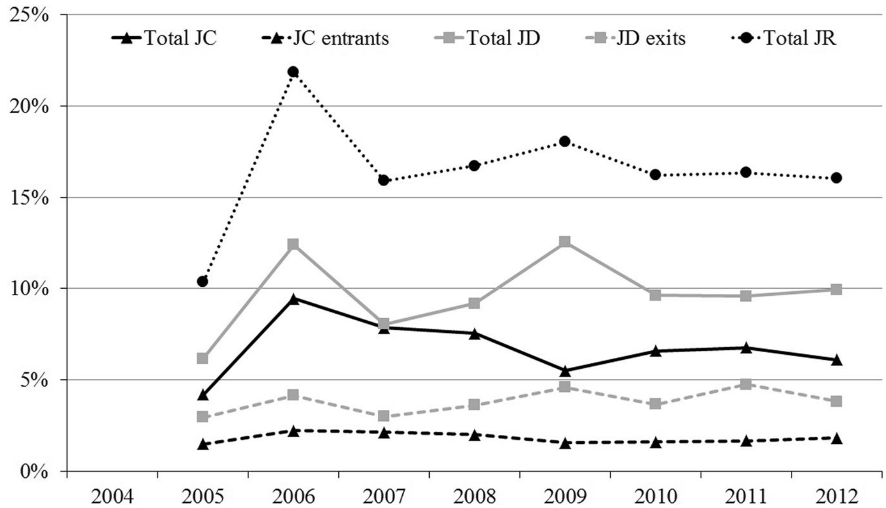

Fig. 4 Job creation and job destruction. *Note*: JC, JD, and JR denote job creation, job destruction and job reallocation, respectively (in percentage)

All this evidence does not seem to be too favourable to the hypothesis that the Portuguese financial crisis has generated an increased job reallocation. We do not therefore reject our hypothesis 1.

4.2 The effect of entry and exit on aggregate productivity growth

Given the observed resource reallocation process, a key issue is whether the crisis generates productive cleansing or counterproductive destruction. Due to large differences in TFP measures across industries, we need to control for industry heterogeneity in any comparison exercise across industries. Figure 5 shows the normalized productivity gap among continuing, entering and exiting firms. As can be seen, the productivity of both continuing and entering firms is higher than that of exiting firms. In other words, less productive firms have been replaced by more productive units. Furthermore, the productivity gap between new firms and exiting firms seems to be higher in the crisis period. The productivity level required for entry during the crisis is even higher than that of continuing firms. It seems therefore that due to stringent financial constraints, crisis may have inhibited potentially good investment projects to flourish, thus reducing aggregate productivity growth.

Table 6 shows the average productivity for entering/exiting firms relative to continuing firms. This time, the TFP measures should be interpreted as the deviation from the TFP of continuing firms (industry-year average). The results are interesting. Firstly, entering firms are, on average, more productive than exiting firms except in two cases (in the *Beverages* and *Computer* sectors). Secondly, in the crisis period, the TFP level of entering firms is higher than the TFP of continuing firms in 17 out of 22 industries (vis-à-vis 5 in the pre-crisis period), which suggests the presence of the credit constraint effect. Finally, looking at corresponding annual values in Table 14, the average productivity of exiting firms is higher than that of continuing firms in almost 16 % of the cases, which is symptomatic of a failure in the market selection mechanism.

Small and large firms may differ in their competitive environment (Chen and Hambrick 1995; Egeln et al. 1997). Thus, an interesting issue is whether these productivity differences across exiting and continuing firms are related to firm size. In Table 7, we compare the productivity of entering and exiting units, respectively, with the productivity of continuing firms in the corresponding size group. One interesting finding is that the average productivity of exiting microenterprises is lower than that of continuing firms, while there is a positive productivity gap in the case of the

Footnote 5 continued
firms with 10–49 employees, medium firms with 50–249, and large firms with 250 or more employees.

Table 4 Job creation and destruction by industry

	Pre-crisis				Crisis			
	JC (%)	Share due to entrants	JD (%)	Share due to exits	JC (%)	Share due to entrants	JD (%)	Share due to exits
Food	8.4	0.299	6.4	0.322	7.2	0.246	8.4	0.346
Beverages	7.1	0.127	7.4	0.157	8.0	0.161	8.8	0.196
Textiles	5.1	0.296	10.1	0.317	4.6	0.303	11.5	0.438
Apparel	7.3	0.363	11.6	0.552	7.5	0.425	14.0	0.605
Leather	8.3	0.361	12.4	0.510	8.7	0.319	8.3	0.523
Wood	6.7	0.244	8.2	0.388	6.0	0.305	12.0	0.365
Paper	3.9	0.283	7.2	0.282	5.0	0.243	5.9	0.381
Printing	7.2	0.318	8.5	0.499	5.3	0.318	11.9	0.430
Chemicals	4.6	0.326	5.7	0.199	4.7	0.268	6.8	0.263
Pharmaceutical	7.4	0.302	6.6	0.194	6.1	0.102	5.0	0.242
Rubber	5.8	0.146	6.5	0.329	5.6	0.150	7.3	0.292
Other non-metallic	5.7	0.253	9.1	0.365	3.9	0.238	10.7	0.348
Basic metals	8.4	0.479	5.5	0.150	4.2	0.157	7.5	0.230
Metals	9.3	0.263	8.1	0.412	7.4	0.214	10.2	0.312
Computer	5.8	0.132	9.5	0.361	5.4	0.143	8.9	0.156
Electrical	6.7	0.136	7.4	0.311	6.5	0.092	6.4	0.277
Machinery	6.4	0.146	6.3	0.307	5.2	0.165	8.5	0.366
Motor vehicles	5.0	0.096	8.8	0.138	5.2	0.118	8.5	0.184
Other transport	7.0	0.209	6.5	0.305	7.4	0.228	18.2	0.397
Furniture	8.2	0.368	10.6	0.444	7.4	0.309	12.8	0.419
Other manufacturing	7.9	0.290	9.1	0.377	6.8	0.236	9.1	0.410
Repair	11.6	0.260	6.9	0.217	9.3	0.304	11.1	0.248

The reported job creation (destruction) rates are calculated as the ratio of job creation (destruction) flows to the average employment of years t and $t-1$, as suggested by Davis et al. (1996). JC and JD denote job creation and destruction rates, respectively. The corresponding values by year are given in Table 13

exit of large firms, suggesting a failure of the market selection mechanism. Indeed, according to the cleansing argument, increased selection created by falling demand is supposed to eliminate low-productivity firms, while high-productivity firms should be expected to engage in productivity-enhancing investments to maintain their competitive position. As suggested by Barlevy (2003), one plausible explanation can be that the largest (and eventually most productive) projects face tighter financial constraints, since in recessions it is hard to find lenders willing to provide large amounts of credit, and therefore projects that require less credit might have a higher chance of survival regardless of their underlying efficiency.

Finally, we analyse the changes in aggregate productivity. Since the process of creative destruction may take time, the decomposition was conducted using two four-year periods, that is, 2004–2008 and 2008–2012. The results of the dynamic Olley–Pakes decomposition exercise, by industry and for the aggregate manufacturing sector, are given in Table 8 and Fig. 6, respectively. While the aggregate TFP growth rate remained more or less constant across the two periods, at 1.2 and 1.1 %, respectively, the change in productivity is pro-cyclical in 60 % of the 22 industries. Note that according to the cleansing paradigm, we should expect a countercyclical productivity growth as a result of the presumably dominant contribution in recessions of the covariance and exit terms, on the one hand, and a reduced impact of the within and entry terms, on the other. The results in Fig. 6 are, however, only partially consistent with

Table 5 Job creation and destruction by firm size

	Pre-crisis					Crisis				
	Rate (%)	Share due to:				Rate (%)	Share due to:			
		Micro	Small	Medium	Large		Micro	Small	Medium	Large
Job creation	7.2	0.225	0.372	0.266	0.137	6.5	0.225	0.379	0.258	0.138
Job destruction	8.9	0.254	0.336	0.272	0.137	10.2	0.273	0.364	0.252	0.111

Micro, small, medium, and large enterprises are those with less than 10, 10–49, 50–249, and 250 or more employees, respectively

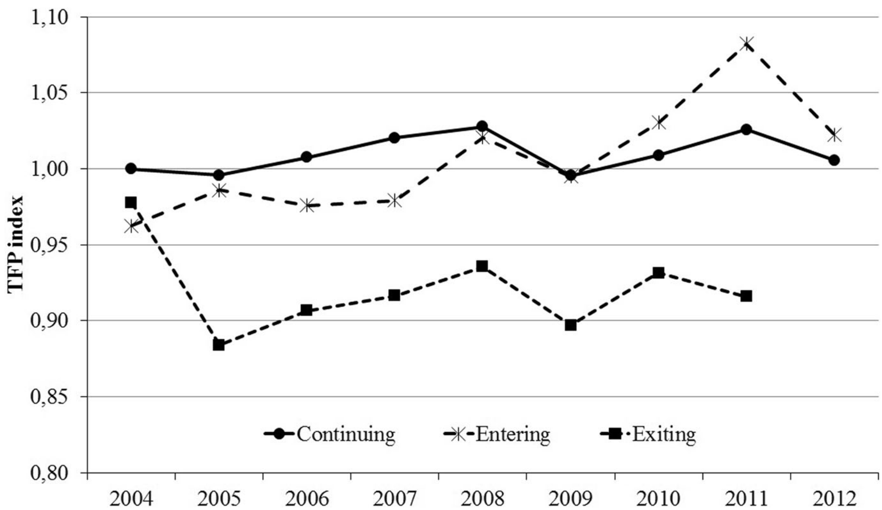

Fig. 5 Productivity of continuing, entering, and exiting firms. *Notes*: Average weighted by firm's output. TFP normalized by the average (total factor) productivity of continuing firms over the sample period at industry-level. The productivity index is set to 1 for continuing firms (in 2004)

the cleansing hypothesis. The strong increase in the covariance term during the crisis suggests that firms with a large decline in productivity have a higher contraction in output as well. In turn, the (large) negative within term indicates that the crisis does generate a sizeable counterproductive destruction.

The main findings are essentially the same if one looks at the decomposition results by industry in Table 8. The covariance term is mostly positive (it is only negative in 4 out of 22 industries) and larger during the crisis. In contrast, the within-firm TFP growth is slightly negative in half of the cases in the pre-crisis period and clearly negative during the crisis. The exit term is also negative (except in three cases in each period), which suggests that exiting firms were relatively more productive than continuing firms. Finally, the net entry figures are mostly positive in both periods due to the positive entry contribution to industry-level TFP growth. Apparently, as can be seen by comparing Fig. 5 and Table 6, there are fewer entrants in the crisis period, but they are on average more productive than the continuing counterparts.

Overall, the data do not seem to clearly support the cleansing effect. Even if low-productivity continuing firms contract market shares and new firms are relatively more productive than continuing firms, a result that is favourable to the cleansing hypothesis, there is a non-negligible number of high-productivity firms that do actually exit, which is a rather clear confirmation of our hypothesis 2. These results are much in line with those reported by Hallward-Driemeier and Rijkers (2013) for the 1997 Indonesian crisis.

4.3 Firm exit, employment change and financial constraints

As discussed in Sect. 2, on reason for the failure of market selection mechanisms is that credit market

Table 6 Productivity gap relative to continuing firms

	Pre-crisis		Crisis	
	Entering firms	Exiting firms	Entering firms	Exiting firms
Food	0.899	0.924	0.915	0.888
Beverages	0.817	0.933	0.904	0.981
Textiles	1.087	0.928	1.094	0.896
Apparel	0.963	0.885	1.024	0.925
Leather	1.057	0.859	1.079	0.899
Wood	0.990	0.979	1.050	0.927
Paper	0.981	0.946	1.085	0.942
Printing	0.900	0.883	0.955	0.872
Chemicals	1.103	0.930	1.018	0.929
Pharmaceutical	1.270	1.187	0.949	1.013
Rubber	1.068	0.897	1.074	0.980
Other non-metallic	0.993	0.913	1.048	0.899
Basic metals	0.985	0.968	1.134	1.077
Metals	1.001	0.931	1.030	0.906
Computer	0.775	0.832	0.910	0.967
Electrical	1.124	0.937	1.039	0.958
Machinery	1.075	0.991	1.084	0.919
Motor vehicles	0.957	0.930	1.014	0.900
Other transport	1.047	0.929	1.045	0.824
Furniture	0.947	0.925	1.019	0.908
Other manufact.	0.891	0.893	1.025	0.885
Repair	0.981	0.884	1.087	0.929

Unweighted averages. For each industry and year, the total factor productivity of entering (exiting) firms is expressed relatively to continuing firms. The corresponding values by year are given in Table 14

distortions in crisis substantially reduce resource reallocation efficiency. To test whether exit among high-productivity/financially constrained firms is more likely in crisis than in pre-crisis period, we estimate model (2). The results are presented in column (1) of Table 9, with the descriptive statistics and the correlation matrix of covariates given in Tables 15 and 16 in "Appendix", respectively.[6] As our dependent variable is the hazard rate, a negative coefficient implies that the corresponding variable reduces the instantaneous likelihood of exit, thus increasing the chance of survival. The null that the parameters are jointly equal to zero is rejected at the 0.01 level.

The productivity coefficient is negatively signed, and it is statistically significant at the 0.01 level, a confirmation that a higher productivity level does reduce the hazard rate. The magnitude of the productivity effect is nevertheless quite distinct across the two periods. The crisis seems to intensify the creative destruction process: in the pre-crisis period, a 1 % increase in the (log) TFP implies a 0.24 % fall in the hazard rate ($=[1-\exp(-0.280)] \times 1\,\% = (1-0.76) \times 1\,\% = 0.24\,\%$), all else constant; in the crisis period, the corresponding reduction in the hazard rate is only 0.10 % ($=[1-\exp(-0.428+0.178)] \times 1\,\% = (1-0.90) \times 1\,\% = 0.10\,\%$). That is, in 2008–2012 it is required an increase of 2.5 % in productivity (rather than 1 % in the pre-crisis) to obtain a 0.24 % increase in the hazard. This is in accordance with the cleansing hypothesis, since firms with a lower productivity level have an increased risk of failure in the crisis period.

All else constant, financially constrained firms seem to be more likely to shut down. Firstly, all three proxies for financial constraints (i.e. *sales*, *operating cash-flow* and *leverage*) are statistically significant at the 0.01 level; and secondly, while the negative sign of the *sales* and *operating cash-flow* coefficients indicate that internal funds reduce the risk of exiting, the positive sign of leverage suggests that dependence on external financing increases the risk. But the impact of these proxies on the hazard seems to be different over the cycle. Indeed, the probability of shutting-down in crisis is lower for those firms able to generate funds internally (*crisis* × *sales* and *crisis* × *operating cash-flow* coefficients are negative; the latter is not statistically significant). In turn, the coefficient of the *crisis* × *leverage* interaction term is negative and statistically significant at the 0.01 level. One plausible interpretation for the latter result is that in the context of general credit constraints firms that have a relatively higher debt level seem to have an increased degree of survivability.

The analysis in Sect. 4.2 revealed that a non-negligible number of large/high-productivity firms did shut down. Thus, to test whether credit constraints are bidding in the case of large firms, column (2) of Table 9 presents a regression that includes *leverage* variable interacted with firm size dummies. As can be seen, the pattern of *leverage* variable is robust to using the size dummies,

[6] The model was implemented using the *stcox* command of Stata SE 11.2, with the *efron* and *shared* options.

Table 7 Productivity gap relative to continuing firms by firm size

	Pre-crisis								Crisis							
	Entering firms				Exiting firms				Entering firms				Exiting firms			
	Micro	Small	Medium	Large	Micro	Small	Medium	Large	Micro	Small	Medium	Large	Micro	Small	Medium	Large
Food	0.838	0.894	0.791	0.931	0.880	0.836	0.861	*1.005*	0.859	0.934	0.919		0.842	0.901	0.906	0.878
Beverages	0.756	0.715			0.836	*1.045*	*1.439*	*1.207*	0.849	0.834	*1.032*		0.936	0.798	0.388	
Textiles	0.936	*1.190*	0.960		0.841	0.898	0.926	0.703	0.965	*1.170*	0.867		0.817	0.918	0.821	0.957
Apparel	0.856	0.998	*1.063*		0.823	0.878	0.854	0.785	0.953	*1.015*	0.758		0.852	0.977	0.888	0.821
Leather	0.958	*1.068*	*1.155*		0.796	0.853	0.883		0.999	*1.025*	*1.064*		0.800	0.924	*1.170*	*1.340*
Wood	0.938	0.990	*1.047*		0.933	*1.033*	0.760		*1.013*	0.869		0.690	0.904	0.853	0.901	
Paper	0.826	*1.053*	0.960		0.833	0.876	*1.026*		0.921	0.910	0.930		0.809	0.942	0.909	
Printing	0.859	0.918	0.786		0.866	0.780	0.749		0.912	0.938	0.678		0.840	0.932	0.866	
Chemicals	0.933	*1.101*		*2.049*	0.803	0.918			0.905	0.775	0.826		0.808	0.880	*1.014*	
Pharmaceutical	0.954	0.931	0.920		0.851	0.862	*1.148*		0.645	0.760	0.721		0.745	0.892	0.563	
Rubber	0.934	0.962	*1.119*		0.808	0.831	0.907	0.814	0.953	0.925	0.734		0.909	0.884	0.833	
Other non-metallic	0.916	0.911	0.680		0.864	0.812	*1.048*	*1.110*	0.976	0.929	0.557		0.849	0.867	0.801	*1.043*
Basic metals	0.889	0.730	*2.448*	0.942	0.854	0.896			0.973	*1.264*			0.970	0.869	0.823	
Metals	0.946	*1.025*	*1.148*		0.893	0.950	0.742		0.973	*1.109*	*1.312*		0.869	0.933	*1.003*	0.726
Computer	0.589	0.993	*1.206*		0.689	0.934	0.859	0.812	0.824	0.677	0.824		0.790	0.917	*1.119*	
Electrical	*1.022*	0.812	0.530		0.864	0.787	0.895		0.895	*1.092*	*2.374*		0.844	*1.140*	0.865	
Machinery	0.947	0.864			0.893	0.827	0.983		0.954	*1.027*	*1.635*		0.834	0.939	0.987	
Motor vehicles	0.833	*1.232*	0.754		0.840	0.978	0.805		0.908	*1.128*	0.388		0.830	0.929	0.793	*1.226*
Other transport	0.930	*1.154*	*1.985*		0.799	*1.232*	0.893		0.942	*1.388*	*1.550*		0.820	0.720	*1.167*	*2.558*
Furniture	0.897	0.907	*1.032*	*1.077*	0.885	0.878	*1.189*	0.997	0.965	*1.061*	0.835	0.148	0.873	0.882	1.094	
Other manufacturing	0.858	0.912	*0.158*		0.866	0.819	*1.342*		0.988	0.957	0.607		0.858	0.818	*1.262*	0.779
Repair	0.963	*1.022*			0.865	0.969	*1.149*		*1.064*	*1.152*	*1.022*		0.918	0.859	0.939	

Unweighted averages. For each size group and by industry-year, the (total factor) productivity of entering (exiting) firms is expressed relatively to continuing firms. Italicized values indicate that the TFP of entering (exiting) firms is greater than that of continuing firms

Table 8 Productivity growth decomposition by industry

	2004–2008					2008–2012				
	Growth	Within	Covariance	Entry	Exit	Growth	Within	Covariance	Entry	Exit
Food	0.015	0.011	−0.009	0.015	−0.002	−0.037	−0.102	0.061	0.015	−0.011
Beverages	−0.002	0.080	−0.065	0.004	−0.021	−0.040	−0.078	0.032	0.006	0.000
Textiles	−0.023	−0.052	0.025	0.028	−0.024	0.076	−0.016	0.079	0.028	−0.014
Apparel	−0.004	−0.028	0.018	0.027	−0.021	0.055	−0.013	0.040	0.034	−0.005
Leather	0.035	−0.015	0.035	0.033	−0.017	0.024	−0.036	0.040	0.022	−0.003
Wood	−0.034	−0.025	−0.010	0.016	−0.014	0.043	−0.056	0.094	0.022	−0.016
Paper	−0.042	−0.084	0.051	0.012	−0.020	0.168	−0.038	0.085	0.147	−0.025
Printing	−0.028	−0.043	−0.005	0.018	0.002	−0.118	−0.193	0.048	0.001	0.025
Chemicals	0.059	0.072	−0.004	0.008	−0.018	−0.084	−0.048	−0.002	−0.017	−0.017
Pharmaceutical	−0.039	0.032	−0.059	0.011	−0.023	−0.156	−0.008	−0.098	−0.002	−0.047
Rubber	−0.010	−0.012	−0.013	0.020	−0.005	−0.034	−0.089	0.056	0.009	−0.010
Other non-metallic	−0.001	0.020	−0.019	0.013	−0.014	−0.036	−0.087	0.043	0.015	−0.008
Basic metals	−0.060	−0.025	−0.011	−0.023	−0.002	0.123	0.001	−0.011	0.136	−0.003
Metals	0.057	0.062	−0.016	0.022	−0.010	0.008	−0.049	0.025	0.025	0.007
Computer	−0.264	−0.303	0.062	0.009	−0.032	0.103	−0.093	0.207	0.008	−0.019
Electrical	0.179	0.070	0.032	0.097	−0.020	−0.157	−0.063	−0.093	0.009	−0.011
Machinery	0.029	−0.030	0.047	0.035	−0.023	0.210	−0.033	0.254	0.014	−0.025
Motor vehicles	0.018	−0.024	0.021	0.013	0.008	0.080	−0.043	0.115	0.008	0.000
Other transport	0.078	0.053	0.003	0.059	−0.037	0.182	0.043	0.197	0.008	−0.066
Furniture	0.059	0.015	0.012	0.012	0.019	−0.117	−0.104	0.041	−0.047	−0.008
Other manufacturing	0.079	−0.013	0.061	0.056	−0.026	−0.098	−0.286	0.145	0.051	−0.009
Repair	0.226	0.155	0.027	0.053	−0.010	0.078	−0.029	0.095	0.031	−0.017

Output-weighted (total factor) productivity growth decomposition at two-digit industry level using the dynamic Olley–Pakes method

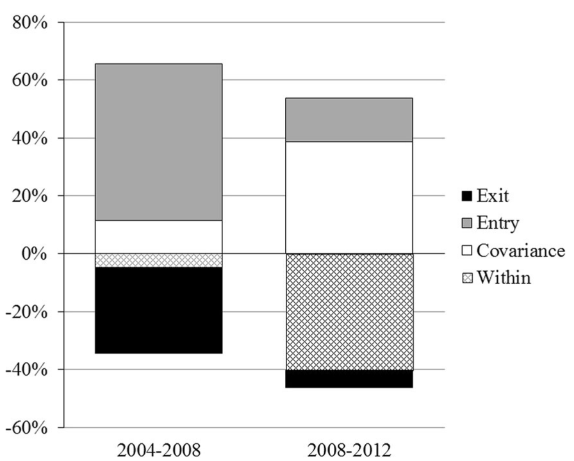

Fig. 6 Productivity growth decomposition (in percentage). *Notes*: Output-weighted (total factor) productivity growth decomposition at the two-digit industry level using the dynamic Olley–Pakes method. Aggregation weighted over 22 two-digit industries by firm's output

except in the case of large firms whose interaction term (i.e. *large* × *leverage*) is not statistically significant. Moreover, the coefficient of the corresponding interaction term (i.e. *large* × *crisis* × *leverage*) shows that if the leverage of large firms increases by 1 %, then the hazard rises by 0.80 %. In other words, while high leverage may be beneficial to firm growth, in deep recessions it may cause serious cash-flow problems in large firms because there might not be enough revenues to cover the relatively higher borrowing costs.

Finally, the *entry rate* does not have any statistically significant impact on the risk of exit, which seems to contradict the expected indirect effect through reduction in the competitive pressure (due to lower entry rate) during the crisis. All else constant, the risk of exit decreases with firm size (proxied by log employment).

To investigate the effect of the financial crisis on employment change of continuing firms, we implement

Table 9 Determinants of firm exit

Variables	(1)	(2)
Log *TFP*	−0.280***	−0.276***
	(0.022)	(0.022)
Crisis × log *TFP*	0.178***	0.176***
	(0.027)	(0.027)
Log *sales*	−0.354***	−0.353***
	(0.011)	(0.011)
Crisis × log *sales*	−0.074***	−0.074***
	(0.009)	(0.009)
Log *operating cash-flow*	−0.101***	−0.100***
	(0.003)	(0.003)
Crisis × log *operating cash-flow*	−0.002	−0.003
	(0.004)	(0.004)
Log *leverage*	0.002***	
	(0.000)	
Micro × log *leverage*		0.002***
		(0.000)
Small × log *leverage*		0.016***
		(0.004)
Medium × log *leverage*		0.117***
		(0.017)
Large × log *leverage*		0.067
		(0.111)
Crisis × log *leverage*	−0.002***	
	(0.000)	
Micro × crisis × log *leverage*		−0.002***
		(0.000)
Small × crisis × log *leverage*		−0.014***
		(0.004)
Medium × crisis × log *leverage*		−0.108***
		(0.017)
Large × crisis × log *leverage*		0.589***
		(0.117)
Entry rate	0.069	0.151
	(1.075)	(1.075)
Log *employment*	−0.343***	−0.350***
	(0.009)	(0.009)
Log likelihood	−179,322.98	−179,276.41
Wald test	15,705.56***	15,956.85***
No. of observations	273,076	273,076

Cox proportional hazard model (2) regression, with 'ties' handled with the method proposed by Efron (1977). The Log *TFP* is normalized by the weighted average (total factor) productivity by industry and *sales* is normalized by firm size. "Crisis" is a dummy for the period 2008–2012. "Micro", "small", "medium", and "large" are dummies for firms with less than 10, 10–49, 50–249, and 250 or more employees, respectively. The regression includes 22 two-digit industry dummies. Firm-cluster robust SEs are given in parentheses

***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

the fixed-effects model (3). The results are presented in Table 10.[7] Despite a relatively small R^2 there is an interesting set of findings. (Note that Hallward-Driemeier and Rijkers 2013, and Carneiro et al. 2014, obtain a R^2 of similar magnitude.) Theoretically, there are two opposite effects connecting productivity and employment. The adoption of new capital-intensive technologies, for example, can generate a reduction in employment. But it can also be expected that through a higher productivity level, firms generate higher profits, which may in turn induce more investment and new jobs. As the table shows, there is a negative and statistically significant effect of productivity on employment change before the crisis but not in the crisis period.

A higher level of *sales* and *operating cash-flow* is associated with job creation, an effect that in the former variable is attenuated during the crisis (the coefficient of the *crisis* × *sales* variable is negative and statistically significant). As expected, the leverage variable has a negative impact on job creation during the crisis (the coefficient of the *crisis* × *leverage* is negative and statistically significant at the 0.05 level; the variable leverage alone is not).

From Tables 9 and 10, we can then conclude that in deep recessions, credit market conditions are an important determinant of firm exit and employment change, as conjectured in our hypotheses 3 and 4.

5 Conclusion

An open question in the literature is whether recessions are periods in which the process of "creative destruction" is particularly fostered. Theory suggests that productive cleansing can be reversed by the nature of the downturn, with deep recessions being mostly seen as periods of "counterproductive" destruction. We used the Portuguese economic crisis to address this issue. By focusing on one particular *bottleneck factor* (i.e. access to external financial resources), we tackle one critical pillar that may constrain the National System of Entrepreneurship performance.

Based on a panel that covers all Portuguese manufacturing firms over the period 2004–2012, our findings

[7] We used the *xtreg* command of Stata SE 11.2, with the *fixed-effects* option. The null hypothesis that the preferred model is random effects is rejected in favour of fixed effects, and the null that all year dummies are jointly equal to zero is also rejected, as well the null in favour of homoscedasticity.

Table 10 Determinants of employment change

Variables	Coefficients
Log *TFP*	−0.975***
	(0.159)
Crisis × log *TFP*	1.367***
	(0.212)
Log *sales*	0.938***
	(0.108)
Crisis × log *sales*	−0.212**
	(0.103)
Log *operating cash-flow*	0.043***
	(0.012)
Crisis × log *operating cash-flow*	0.021
	(0.015)
Leverage	−0.002
	(0.004)
Crisis × *leverage*	−0.015**
	(0.007)
Entry rate	−4.138
	(3.430)
Log *employment*	−4.329***
	(0.142)
No. of observations	274,235
No. of firms	50,604
F statistic	68.14***
R^2	0.028
Adjuster R^2	0.028

Fixed-effects regression of model (3). "Crisis" is a dummy for the period 2008–2012. The Log *TFP* is normalized by the weighted average (total factor) productivity by industry and *sales* is normalized by firm size. All regressions include 22 two-digit industry dummies, eight-year dummies and constant term. Firm-cluster robust SEs are given in parentheses

***, **, * Statistical significance at the 0.01, 0.05, and 0.10 levels, respectively

only partially support the cleansing hypothesis. The average entry rate slightly decreases during the crisis, while the exit rate is clearly higher. There is a slowdown in job creation and an increase in job destruction, but with no evidence that job reallocation is strongly countercyclical. On the other hand, as predicted by the cleansing hypothesis, decomposition of aggregate productivity growth reveals that low-productivity continuing firms have their market shares reduced during the crisis, thus enhancing productivity growth. However, deep recessions can also be counterproductive, with the possible exit of large/high-productivity firms, and we do actually observe this result in the data.

One plausible explanation for the observed market selection pattern during the Portuguese financial crisis is the presence of credit market distortions, that is, credit constraints (and banking practices) with the ability to reduce efficiency in resource reallocation and productivity growth. Indeed, although we confirm that low-productivity firms have a lower probability of survival, credit market conditions do play a role in firm exit, especially in the case of large firms. Moreover, high external funding dependence during the crisis seems to be adversarial to employment creation.

Gaining insight into the mechanisms through which deep recessions impact firm dynamics is important for economic modelling and policy making as well. Our results show that in deep recessions, very harsh credit market conditions have the notable disadvantage of running the risk of throwing out the promising baby with the bath water, thus impairing the post-crisis economic recovery. *Bottleneck factors* do therefore matter and countercyclical policies to ensure adequate access to external funding are, as a result, of special relevance.

Our analysis focused on one ("output") measure of the national system of entrepreneurship performance, namely the firm-level productivity growth generated by firm mobility in a scenario of deep recession. Other components of a highly complex system are thus ignored and left for the future agenda. Among them are of special relevance the issues related with the micro mechanisms by which financial crisis impact the process of creative destruction. This would require proper micro-foundation modelling that is beyond the scope of this article. Without this type of modelling, it is perhaps unclear the degree to which countercyclical policies as suggested above are effective. In particular, the uncertainty created by financial crisis is likely to have implied entrepreneurs to postpone productivity-enhancing projects, in which case we would have had lack of investment demand rather than an insufficient supply of credit funds. We leave therefore this important aspect for future research. Finally, assessing to what extent our findings can be generalized to other crisis episodes seems also an interesting area for future development.

Appendix

See Tables 11, 12, 13, 14, 15 and 16.

Table 11 Annual entry and exit rates by industry (in percentage)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2004	2005	2006	2007	2008	2009	2010	2011	2012
	Entry rate									Exit rate								
Food	4.3	6.4	7.4	6.2	6.1	5.7	5.7	5.8	7.0		4.7	5.2	4.9	5.8	6.0	4.7	8.1	5.9
Beverages	2.2	5.3	4.7	5.2	7.8	7.4	5.5	6.6	5.2		2.4	2.6	4.0	2.9	4.8	3.8	4.7	4.0
Textiles	3.6	5.3	7.2	6.2	6.0	5.0	4.7	5.3	6.3		8.4	9.7	7.4	9.6	11.0	8.2	10.7	9.9
Apparel	4.2	5.5	7.3	7.3	8.1	7.1	7.2	8.2	8.6		10.8	13.1	8.7	11.1	14.9	12.9	13.7	10.6
Leather	5.3	6.5	9.4	8.0	8.5	6.5	7.9	10.4	9.7		10.3	11.0	9.5	8.6	9.3	7.5	8.8	5.9
Wood	4.2	5.4	5.1	5.6	6.2	5.5	4.8	6.2	7.0		8.2	9.1	7.3	8.3	10.0	7.8	10.8	7.9
Paper	2.5	4.9	4.4	4.8	6.5	6.9	3.9	5.5	4.8		6.5	7.3	7.3	7.3	8.3	6.7	8.9	7.4
Printing	4.8	6.8	7.7	6.7	6.6	5.3	4.3	4.6	5.4		6.3	8.0	7.6	8.0	7.8	6.8	11.4	7.4
Chemicals	3.5	5.0	5.7	4.9	7.2	5.8	4.0	4.1	5.8		5.4	6.6	7.1	7.9	7.4	7.2	7.9	5.1
Pharmaceutical	1.9	10.3	7.0	9.8	6.7	2.8	4.7	10.2	5.0		2.8	6.9	4.3	4.1	6.7	4.7	3.8	6.5
Rubber	3.5	4.3	4.4	5.8	4.8	4.7	5.0	5.6	4.3		4.8	5.8	4.7	6.1	7.5	4.3	7.6	6.0
Other non-metallic	3.0	4.8	4.9	5.2	4.1	3.9	3.6	3.5	4.5		6.3	7.8	6.0	6.0	8.1	7.6	9.9	8.1
Basic metals	1.1	6.0	2.6	5.7	6.4	7.4	3.6	4.7	7.6		6.0	6.4	8.5	6.8	8.7	5.5	7.9	6.8
Metals	4.5	5.4	6.7	6.5	5.9	4.6	5.0	5.3	5.4		6.6	7.5	6.2	6.2	6.6	5.3	9.1	6.2
Computer	5.4	6.9	9.0	6.1	9.0	6.9	4.6	8.4	7.3		10.0	13.0	10.0	9.0	9.4	7.9	9.2	5.3
Electrical	3.8	5.1	4.2	6.8	5.7	5.3	4.7	6.1	5.3		8.9	8.2	8.6	7.8	6.1	5.5	10.0	6.1
Machinery	2.8	5.2	5.9	5.1	4.8	4.0	3.3	4.8	5.7		7.8	8.4	6.2	6.5	6.7	5.8	8.2	7.7
Motor vehicles	2.8	4.8	6.1	4.7	6.5	4.8	4.9	2.3	4.2		6.8	5.0	5.2	4.7	7.4	3.3	8.4	7.8
Other transport	4.4	6.4	8.8	9.3	10.3	5.6	3.7	10.3	10.0		11.1	14.6	8.8	8.7	12.1	9.8	10.4	6.6
Furniture	3.9	5.6	6.5	6.3	6.6	5.8	5.6	6.8	6.4		5.9	8.9	8.1	8.9	9.0	8.0	12.0	10.0
Other manufacturing	5.2	5.9	7.5	6.7	7.0	5.0	4.9	5.9	6.9		7.1	10.1	6.6	7.5	7.9	6.6	8.9	7.6
Repair	5.8	7.8	8.7	7.5	7.3	9.0	9.4	11.8	10.1		2.3	3.6	4.0	5.4	7.7	5.7	9.7	7.0

See notes to Table 2

Table 12 Survival rate by industry (in percentage)

Entry Cohort	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
	Food								Beverages								Textiles							
2004	92.1	81.8	72.9	68.0	63.5	59.6	53.7	48.8	100	84.6	76.9	76.9	69.2	69.2	69.2	61.5	91.6	86.7	78.3	72.3	57.8	49.4	42.2	38.6
2005	100	86.5	77.1	69.4	60.6	58.4	55.2	50.3	100	93.8	90.6	81.3	71.9	65.6	62.5	62.5	100	87.5	78.3	67.5	57.5	49.2	43.3	41.7
2006		100	92.3	83.0	76.1	72.5	62.1	58.2		100	86.2	82.8	82.8	79.3	86.2	82.8		100	87.3	75.8	66.9	60.5	47.1	36.9
2007			100	86.5	77.1	72.6	64.5	57.7			100	93.9	81.8	78.8	78.8	75.8			100	83.0	64.4	57.8	43.0	32.6
2008				100	89.5	80.0	70.2	64.9				100	90.4	82.7	78.8	78.8				100	89.6	80.0	73.6	60.8
2009					100	90.8	76.1	68.0					100	92.2	86.3	80.4					100	87.8	71.4	64.3
2010						100	83.4	73.1						100	94.7	92.1						100	85.4	75.3
2011							100	91.6							100	95.8							100	91.4
	Apparel								Leather								Wood							
2004	91.6	76.1	66.8	61.3	51.3	39.9	34.5	30.3	91.6	76.1	66.8	61.3	51.3	39.9	34.5	30.3	91.7	81.8	69.7	60.6	50.0	44.7	40.2	39.4
2005	100	83.8	71.3	62.8	48.6	41.9	34.8	30.4	100	83.8	71.3	62.8	48.6	41.9	34.8	30.4	100	83.0	77.6	66.1	56.4	51.5	41.2	37.6
2006		100	88.8	76.3	59.1	46.3	35.7	30.8		100	88.8	76.3	59.1	46.3	35.7	30.8		100	78.7	68.0	56.7	44.7	34.0	32.7
2007			100	85.0	64.6	53.2	42.3	37.3			100	85.0	64.6	53.2	42.3	37.3			100	84.3	71.7	61.6	47.8	40.3
2008				100	81.7	66.5	54.6	48.2				100	81.7	66.5	54.6	48.2				100	80.9	69.9	61.3	54.3
2009					100	88.7	68.7	60.0					100	88.7	68.7	60.0					100	90.5	79.6	68.7
2010						100	87.2	76.1						100	87.2	76.1						100	78.9	73.2
2011							100	85.5							100	85.5							100	81.3
	Paper								Printing								Chemicals							
2004	72.7	54.5	54.5	45.5	45.5	45.5	36.4	36.4	93.3	81.9	78.1	67.6	61.0	55.2	50.5	46.7	100	82.4	76.5	64.7	58.8	58.8	58.8	58.8
2005	100	100	81.0	71.4	57.1	57.1	42.9	42.9	100	88.0	74.0	66.0	60.0	52.0	45.3	40.7	100	66.7	58.3	45.8	45.8	41.7	45.8	41.7
2006		100	100	94.4	66.7	55.6	55.6	50.0		100	85.2	74.6	68.6	60.4	49.1	43.8		100	88.9	81.5	66.7	59.3	55.6	55.6
2007			100	78.9	57.9	52.6	47.4	42.1			100	83.6	71.9	66.4	52.7	47.9			100	82.6	60.9	43.5	39.1	39.1
2008				100	92.3	84.6	76.9	73.1				100	85.1	75.9	58.9	53.9				100	81.8	69.7	57.6	51.5
2009					100	88.9	74.1	66.7					100	94.6	76.8	69.6					100	80.8	76.9	69.2
2010						100	93.3	86.7						100	86.4	75.0						100	64.7	47.1
2011							100	90.0							100	94.3							100	100
	Pharmaceutical								Rubber								Other non-metallic							
2004	100	100	50.0	0.0	0.0	0.0	0.0	0.0	87.9	78.8	72.7	69.7	60.6	54.5	54.5	48.5	92.1	82.0	76.4	71.9	64.0	53.9	49.4	46.1
2005	100	91.7	91.7	83.3	83.3	83.3	66.7	50.0	100	85.0	77.5	70.0	60.0	60.0	52.5	52.5	100	79.0	69.6	65.2	59.4	50.0	43.5	40.6
2006		100	87.5	87.5	75.0	75.0	62.5	62.5		100	87.8	85.4	73.2	61.0	43.9	39.0		100	79.4	69.9	61.8	50.7	41.2	40.4
2007			100	75.0	66.7	58.3	33.3	25.0			100	79.6	66.7	63.0	48.1	42.6			100	86.1	66.0	58.3	47.9	46.5

Table 12 continued

Entry Cohort	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
2008				100	100	87.5	87.5	87.5				100	77.3	68.2	56.8	52.3				100	81.1	65.8	55.9	50.5
2009					100	100	100	66.7					100	97.6	78.6	66.7					100	86.3	68.6	65.7
2010						100	80.0	60.0						100	95.6	82.2						100	82.0	64.0
2011							100	81.8							100	83.7							100	72.8
	Basic metals								Metals								Computer							
2004	92.1	82.0	76.4	71.9	64.0	53.9	49.4	46.1	90.1	77.6	70.4	63.9	60.5	57.1	49.0	45.9	92.3	69.2	61.5	61.5	53.8	53.8	38.5	38.5
2005	100	79.0	69.6	65.2	59.4	50.0	43.5	40.6	100	85.7	76.8	72.8	66.2	61.9	54.2	49.0	100	62.5	31.3	31.3	25.0	25.0	18.8	18.8
2006		100	79.4	69.9	61.8	50.7	41.2	40.4		100	88.8	79.9	71.7	66.6	55.6	51.6		100	85.0	65.0	50.0	45.0	40.0	35.0
2007			100	86.1	66.0	58.3	47.9	46.5			100	88.5	78.4	73.4	65.0	59.7			100	76.9	69.2	61.5	46.2	46.2
2008				100	81.1	65.8	55.9	50.5				100	90.2	82.5	69.8	63.7				100	78.9	63.2	63.2	57.9
2009					100	86.3	68.6	65.7					100	91.1	76.6	68.7					100	85.7	78.6	64.3
2010						100	82.0	64.0						100	86.8	79.1						100	100	100
2011							100	72.8							100	90.0							100	93.8
	Electrical								Machinery								Motor vehicles							
2004	81.8	77.3	68.2	63.6	59.1	59.1	59.1	50.0	75.7	59.5	56.8	56.8	48.6	43.2	40.5	29.7	91.7	83.3	75.0	66.7	58.3	58.3	75.0	75.0
2005	100	82.1	67.9	64.3	67.9	64.3	53.6	46.4	100	79.1	70.1	67.2	61.2	53.7	47.8	40.3	100	85.0	75.0	75.0	55.0	55.0	45.0	40.0
2006		100	68.2	59.1	45.5	45.5	40.9	36.4		100	86.5	79.7	67.6	60.8	50.0	45.9		100	84.6	76.9	65.4	57.7	57.7	46.2
2007			100	82.9	80.0	74.3	60.0	45.7			100	85.7	73.0	68.3	58.7	58.7			100	65.0	55.0	55.0	45.0	40.0
2008				100	89.7	79.3	58.6	55.2				100	89.8	76.3	64.4	50.8				100	85.7	78.6	53.6	50.0
2009					100	73.1	57.7	57.7					100	93.5	84.8	78.3					100	90.0	70.0	60.0
2010						100	82.6	78.3						100	86.5	81.1						100	71.4	61.9
2011							100	89.7							100	92.3							100	88.9
	Other transport								Furniture								Other manufacturing							
2004	87.5	75.0	62.5	50.0	25.0	37.5	37.5	37.5	90.4	80.8	69.2	62.5	55.8	51.0	43.3	38.5	93.3	77.3	69.3	62.7	61.3	58.7	49.3	44.0
2005	100	54.5	54.5	45.5	45.5	27.3	27.3	27.3	100	90.5	80.4	68.2	62.2	56.1	45.3	39.9	100	83.3	64.3	58.3	51.2	48.8	45.2	45.2
2006		100	85.7	71.4	64.3	57.1	28.6	21.4		100	87.0	75.7	68.6	64.5	55.6	47.9		100	85.4	69.9	58.3	49.5	45.6	43.7
2007			100	86.7	80.0	53.3	40.0	40.0			100	86.3	71.9	64.4	51.3	43.8			100	85.9	80.4	73.9	56.5	50.0
2008				100	76.5	70.6	64.7	47.1				100	83.4	74.8	62.0	55.2				100	87.5	79.2	66.7	60.4
2009					100	75.0	75.0	62.5					100	89.3	75.7	65.7					100	87.9	77.3	71.2
2010						100	80.0	100						100	82.3	82.3						100	87.3	79.4
2011							100	92.9							100	86.7							100	87.8

Table 12 continued

Entry Cohort	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
	Repair																							
2004	97.3	93.3	92.0	86.7	81.3	77.3	65.3	64.0																
2005	100	94.4	85.2	82.4	77.8	73.1	62.0	60.2																
2006		100	89.7	83.3	73.8	68.3	57.1	51.6																
2007			100	90.3	84.1	73.5	57.5	46.0																
2008				100	89.3	83.0	70.5	62.5																
2009					100	93.2	81.5	71.9																
2010						100	87.3	81.0																
2011							100	92.6																

See notes to Table 3

Table 13 Annual job creation and destruction rates by industry (in percentage)

	2005	2006	2007	2008	2009	2010	2011	2012	2005	2006	2007	2008	2009	2010	2011	2012
	Job creation rate								Job destruction rate							
Food	4.4	11.7	9.0	8.5	7.0	7.5	6.4	6.6	3.8	9.4	6.0	8.2	8.3	7.2	8.9	9.3
Beverages	2.7	10.9	7.7	14.6	4.5	6.2	10.2	4.4	4.0	11.4	6.7	12.9	9.0	8.4	6.9	6.8
Textiles	3.3	6.3	5.6	4.5	4.2	4.7	5.0	4.4	7.7	13.0	9.6	11.9	13.8	10.7	9.1	11.8
Apparel	3.8	10.0	8.2	8.2	5.9	7.8	8.2	7.5	8.8	15.7	10.3	12.4	19.0	13.3	13.7	11.4
Leather	5.6	11.2	8.2	7.7	6.3	8.8	10.9	9.6	9.2	16.8	11.0	8.9	9.9	9.3	6.5	6.8
Wood	3.9	9.6	6.5	6.6	4.4	6.5	7.3	5.3	4.7	12.2	7.8	10.0	17.1	10.6	11.6	10.6
Paper	2.3	4.4	5.0	4.2	6.8	4.3	5.0	4.8	4.4	10.6	6.5	4.9	6.5	6.8	4.1	7.5
Printing	4.9	9.5	7.0	7.0	5.4	4.6	4.1	5.2	3.8	12.2	9.5	9.9	12.5	9.7	14.5	12.7
Chemicals	3.8	5.0	5.1	6.6	3.1	6.3	3.0	4.7	5.2	6.9	4.9	4.5	9.7	6.1	6.1	7.5
Pharmaceutical	9.0	7.0	6.3	7.8	8.3	4.9	4.4	5.3	5.4	6.9	7.4	3.5	8.6	5.0	2.7	5.2
Rubber	4.6	7.2	5.5	7.1	3.2	6.8	6.0	4.8	4.0	8.9	6.6	7.6	11.0	5.5	6.5	6.0
Other non-metallic	3.0	7.9	6.1	4.1	3.9	4.0	3.7	3.7	6.5	12.9	7.8	9.6	12.1	9.6	8.5	13.5
Basic metals	10.1	6.7	8.5	4.9	2.6	3.7	4.6	5.0	3.8	7.1	5.6	5.3	13.6	4.5	4.1	10.0
Metals	4.5	12.2	11.1	9.0	6.7	7.0	8.1	6.0	5.1	11.0	8.1	7.6	10.4	9.5	12.3	11.1
Computer	4.4	10.2	2.8	6.2	3.7	6.8	6.3	4.3	12.6	7.0	9.0	8.5	11.2	15.7	4.7	4.6
Electrical	5.6	7.0	7.4	11.5	8.5	5.6	3.8	3.2	4.3	13.2	4.7	7.5	7.2	4.5	6.6	6.4
Machinery	3.6	8.6	7.0	6.1	4.0	4.8	5.2	5.8	4.7	9.3	5.0	7.3	11.2	8.1	7.8	8.1
Motor vehicles	2.5	5.7	6.8	6.9	1.3	5.2	6.4	6.2	7.0	11.9	7.4	5.1	17.6	10.1	5.5	4.4
Other transport	3.3	9.0	8.7	8.7	5.1	5.6	7.9	9.6	6.2	8.7	4.5	11.5	15.1	38.0	14.6	11.9
Furniture	4.9	10.1	9.6	8.5	6.6	8.8	7.3	5.9	4.9	17.7	9.0	12.1	12.9	10.3	12.4	16.1
Other manufacturing	5.5	9.7	8.5	7.8	6.2	6.8	6.2	6.9	5.4	13.9	8.1	8.6	9.3	8.0	7.5	12.2
Repair	6.2	16.0	12.6	10.9	9.7	8.0	8.6	9.2	3.8	10.0	6.9	6.1	14.2	10.6	12.1	12.6

See notes to Table 4

Table 14 Productivity gap relative to continuing firms

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2004	2005	2006	2007	2008	2009	2010	2011	2012
	Entering firms									Exiting firms								
Food	0.905	0.922	0.880	0.888	0.920	0.908	0.910	0.912	0.926	0.936	0.918	0.945	0.898	0.898	0.842	0.927	0.886	
Beverages	0.774	0.863	0.890	0.740	0.869	0.916	0.984	0.904	0.847	0.839	0.936	0.892	1.067	1.219	0.915	0.940	0.849	
Textiles	1.133	1.080	1.120	1.015	1.143	1.055	1.034	1.084	1.153	0.984	0.906	0.951	0.871	0.937	0.844	0.906	0.897	
Apparel	0.954	0.993	0.969	0.935	0.990	1.021	1.014	1.059	1.039	1.004	0.860	0.804	0.872	0.926	0.975	0.914	0.887	
Leather	0.983	1.063	1.110	1.072	1.020	1.077	1.112	1.147	1.039	0.912	0.831	0.850	0.842	0.899	0.921	0.833	0.941	
Wood	0.956	1.023	0.972	1.007	1.023	1.021	1.033	1.113	1.061	1.119	0.904	0.967	0.925	0.899	0.943	0.903	0.964	
Paper	1.017	0.950	0.922	1.035	1.011	0.996	1.357	1.130	0.931	1.021	0.826	0.999	0.940	0.985	0.756	1.038	0.990	
Printing	0.913	0.934	0.894	0.859	0.922	0.954	1.001	0.945	0.953	0.945	0.880	0.818	0.891	0.842	0.856	0.931	0.860	
Chemicals	1.215	1.098	1.041	1.056	1.148	0.916	1.050	1.122	0.854	0.979	0.933	0.961	0.849	0.908	0.856	1.117	0.835	
Pharmaceutical	1.243	1.268	1.112	1.457	0.592	1.022	1.275	0.940	0.914	0.760	1.248	1.320	1.419	0.743	0.638	1.319	1.355	
Rubber	1.144	0.990	1.085	1.055	1.075	0.979	1.178	0.999	1.140	0.963	0.829	0.853	0.942	0.900	1.011	1.101	0.910	
Other non-metallic	1.022	1.027	0.984	0.938	1.058	1.134	0.990	1.055	1.002	0.961	0.922	0.964	0.803	0.944	0.837	0.977	0.836	
Basic metals	0.757	0.847	1.265	1.069	0.864	1.145	1.547	0.908	1.208	1.000	0.952	0.888	1.034	0.969	1.226	1.084	1.031	
Metals	0.959	1.027	1.014	1.002	1.014	1.004	1.059	1.071	1.003	0.956	0.904	0.917	0.947	0.898	0.923	0.932	0.870	
Computer	1.160	0.738	1.030	0.173	1.118	0.985	0.893	0.828	0.725	0.816	0.868	1.073	0.572	1.117	0.822	0.894	1.034	
Electrical	1.137	1.025	1.212	1.122	1.141	0.991	1.169	1.000	0.893	1.176	0.782	0.934	0.854	1.032	0.977	0.911	0.913	
Machinery	1.089	1.175	0.930	1.106	1.049	1.095	1.049	1.206	1.022	0.979	1.005	1.000	0.981	0.978	0.996	0.854	0.850	
Motor vehicles	0.924	0.887	0.986	1.033	0.926	0.809	0.969	1.409	0.958	0.847	0.792	1.059	1.024	1.008	0.800	0.893	0.901	
Other transport	1.566	0.566	1.013	1.044	1.087	1.228	0.874	0.947	1.088	1.065	0.673	1.095	0.882	0.882	1.137	0.591	0.685	
Furniture	0.944	0.999	0.921	0.923	0.995	0.962	0.995	1.064	1.078	0.914	0.931	0.913	0.943	0.910	0.906	0.924	0.891	
Other manufacturing	0.871	0.880	0.883	0.930	0.989	1.060	1.008	1.126	0.944	0.893	0.891	0.894	0.894	0.877	0.893	0.922	0.849	
Repair	0.981	1.030	0.928	0.987	1.003	1.054	1.062	1.168	1.148	0.936	0.874	0.759	0.967	0.917	0.898	0.925	0.974	

See notes to Table 6

Table 15 Descriptive statistics

	Overall	Pre-crisis	Crisis
Log *TFP*	0.274	0.271	0.277
	(0.426)	(0.418)	(0.432)
Log *sales*	10.395	10.357	10.428
	(1.042)	(1.027)	(1.054)
Log *operating cash-flow*	6.379	6.55	6.230
	(4.757)	(4.679)	(4.818)
Log *leverage*	1.229	1.133	1.313
	(30.94)	(22.85)	(36.55)
Log *employment*	1.912	1.955	1.875
	(1.267)	(1.260)	(1.272)
Entry rate	0.059	0.057	0.061
	(0.015)	(0.014)	(0.016)

Mean values and standard deviations, given in parentheses, of variables used in the models (2) and (3). "Overall" refers to pooled yearly values, 2004–2012. The Log *TFP* is normalized by the weighted average (total factor) productivity by industry

Table 16 Correlation across covariates

	[1]	[2]	[3]	[4]	[5]	[6]
[1] *Exit*	1					
[2] Log *TFP*	−0.125*	1				
[3] Log *sales*	−0.222*	0.185*	1			
[4] Log *operating cash-flow*	−0.199*	0.174*	0.441*	1		
[5] Log *leverage*	0.037*	0.001	−0.029*	−0.021*	1	
[6] Log *employment*	−0.147*	−0.226*	0.187*	0.301*	−0.012*	1
[7] *Entry rate*	0.019*	−0.037*	−0.095*	−0.010*	0.001	−0.001

Pooled yearly values, 2004–2012

* Denotes statistical significance at the 0.01 level

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